NOTES AND CORRESPONDENCE

Suggestions in the Observational Record of Land–Atmosphere Feedback Operating at Seasonal Time Scales

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ABSTRACT

Observed monthly precipitation anomalies are standardized across midlatitude land, and ergodicity is invoked to combine the spatially distributed data into probability density functions (pdfs) of precipitation conditioned on the strength of earlier anomalies. The conditional pdfs, though broad and overlapping, are indeed distinct at a high (99.9%) level of confidence. This implies a nonzero degree of predictability for midlatitude precipitation, even at 3-month leads. This behavior is reproduced by an AGCM only when land–atmosphere feedback in the model is enabled.

1. Introduction

Higher-than-average precipitation rates over land typically lead to wetter-than-average soil wetness, which in turn often leads to higher-than-average evaporation rates in subsequent weeks. If this higher evaporation in turn leads to additional rainfall, either directly through local recycling or indirectly through a modification of atmospheric conditions or the large-scale circulation, then the so-called positive land–atmosphere feedback cycle is complete—the high precipitation acts to sustain itself through its interaction with the land surface. Positive land–atmosphere feedback can also take the opposite form, with dry conditions perpetuating themselves through the maintenance of low evaporation rates at the land surface.

Although such feedback is a well-established phenomenon in atmospheric models [see literature review in Koster and Suarez (2003)], evidence that it occurs in nature is highly limited. The problem lies in the demonstration of the final part of the cycle, namely, that anomalous evaporation rates unequivocally induce anomalous rainfall rates. Some analyses of rainfall data in irrigated regions are suggestive (Barnston and Schickedanz 1984), as are analyses of in situ soil moisture and rainfall data (Findell and Eltahir 1997), though these data can be examined in more than one way (Salvucci et al. 2002), with contrasting conclusions.

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Koster et al. (2003), through a mix of observational and model analyses, found evidence supporting the existence of positive feedback along a broad swath spanning the continental United States. They showed that the monthly variances and the submonthly autocorrelations of precipitation inherent in the observational record have distinct patterns that are well reproduced (in shape, if not in magnitude) by an AGCM when land–atmosphere feedback is enabled. When the feedback is artificially disabled in the AGCM, the model's ability to reproduce the patterns is destroyed. Koster et al. (2003) concluded that either positive land–atmosphere feedback does exist in nature or that through pure coincidence, the AGCM reproduces the correct patterns for the wrong reason.

The present study builds on the Koster et al. (2003) study by extending the analysis to global midlatitudes and by focusing on time scales of greater relevance to seasonal prediction. We quantify, through the construction of conditional probability density functions (pdfs), the ability of a rainfall anomaly to affect—or at least correlate with—subsequent rainfall up to three months in the future. We then examine the ability of an AGCM to reproduce the observed conditional pdfs when land–atmosphere feedback is enabled and when it is artificially disabled. Section 2 describes the processing of the observational data, and section 3 provides the observational results. Section 4 presents the model analyses.

Note that some analyses (Findell and Eltahir 2003) suggest the potential for negative land–atmosphere feedback in limited regions, by which wet soil tends to reduce subsequent precipitation. The present paper implicitly focuses on positive feedback. If negative feedback does exist in some places, it would, according to the structure of our analysis, only tend to cancel out some of the effects of positive feedback elsewhere—it would only make the identification of positive feedback in the data that much more difficult.

2. Data

Global monthly precipitation data generated by the Global Precipitation Climatology Project (GPCP) (Huffman et al. 1997) are analyzed in this study. The version 2 dataset, which combines in situ (gauge) and satellite measurements, covers the period 1979–2001 at a spatial resolution of 2.5° × 2.5°.

For this analysis, all precipitation amounts are standardized. If $\overline{P_j}$ is the average precipitation for month j across all years at a given grid cell, and if σ_j is the standard deviation of the monthly totals for month j at the grid cell, then we convert the precipitation $P_{j,n}$ for month j in year n to the corresponding standardized quantity, $P'_{j,n}$:

$$P'_{j,n} = \frac{P_{j,n} - \overline{P_j}}{\sigma_j}. \tag{1}$$

The standardization is motivated by the short (23 yr) data record. Correlations between monthly precipitation rates tend to be low—much too low, in fact, to establish accurately with 23 data pairs. One way around this limitation is the use of anomaly pattern correlation techniques (e.g., Van den Dool 1985; Van den Dool et al. 1986). Here, we instead invoke the principle of ergodicity to combine data from the large number of midlatitude land grid cells into a single, huge sample. This single sample is indeed large enough to allow the construction of pdfs of monthly rainfall conditioned on the rainfall of previous months.

Of course, by invoking ergodicity to study the feedback question, we are implicitly assuming that land–atmosphere feedback operates everywhere the same way. This is highly unlikely and is certainly not supported by AGCM analyses (e.g., Koster et al. 2000). Nevertheless, it is an acceptable assumption to make when testing the null hypothesis, that is, that feedback in nature has no impact at all on precipitation behavior at seasonal time scales. Note that other spatially nonstationary aspects of rainfall (e.g., a geographically varying response to SSTs) may also have an impact on the pdfs. This is unavoidable. The model analysis in section 4, however, will allow us to isolate the impact of land–atmosphere feedback from other such influences on the pdfs, at least for the AGCM's climate.

3. Results

The solid curve in Fig. 1a is the pdf of monthly (standardized) rainfall based on 70 288 data values—values

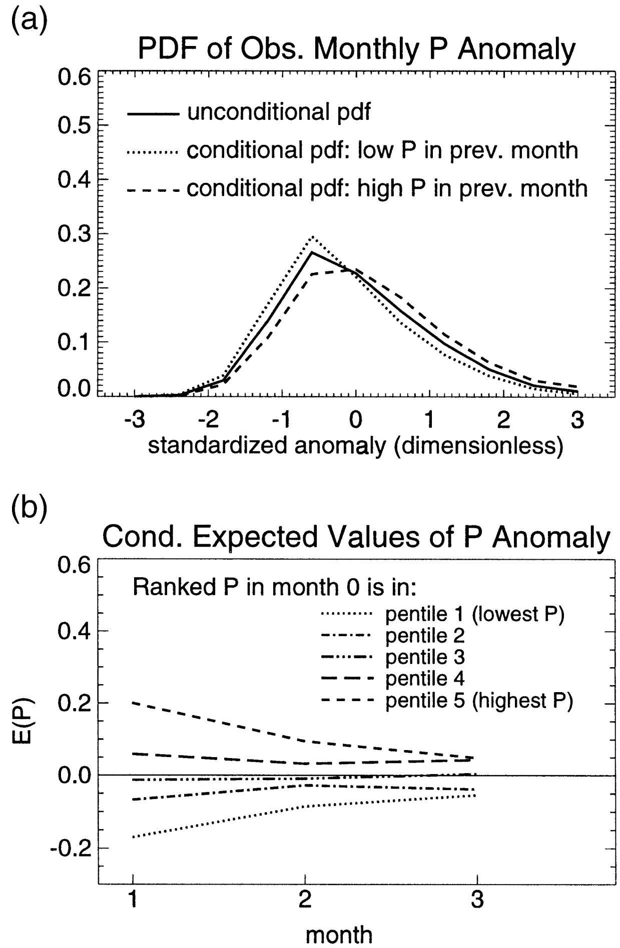

FIG. 1. (a) Pdf of standardized precipitation anomaly in May, Jun, Jul, or Aug (solid curve) and the corresponding pdfs conditioned on low and high prior precipitation (the dotted and dashed curves, respectively) in the previous month. (b) Mean of the conditional pdfs as a function of time. Each curve shows the expected value of the standardized monthly precipitation anomaly 1, 2, and 3 months after an initial ranked anomaly.

sampled across both space (i.e., across 764 land grid cells in boreal midlatitudes, between 30° and 60°N) and time (across 92 monthly values, using May, June, July, and August totals for the years 1979–2001). We focus in this paper on warm-season rainfall because it is the most likely to be affected by land–atmosphere feedback.

The dotted and dashed curves in Fig. 1a represent conditional pdfs based on a binning of the 70 288 precipitation values into five categories, defined as follows: Associated with the precipitation value $P_{m,n}$ in month m of year n at a given grid cell (where m can be May, June, July, or August) is a precipitation amount for the prior month, $P_{m-1,n}$. If $P_{m-1,n}$ is in the lowest fifth of all monthly precipitation amounts at that grid cell for the period in question (i.e., in the lowest fifth of all April, May, June, and July precipitation amounts for the 23 yr studied), then the precipitation value $P_{m,n}$ is assigned to category 1. Similarly, if $P_{m-1,n}$ lies in the second lowest fifth of all precipitation amounts at that cell for the months studied, then $P_{m,n}$ is assigned to category 2. We invoke ergodicity to combine all values for a given category across the globe into a single grouping of data, from which we derive the conditional pdf associated with that category.

The dotted curve shows the conditional pdf for category 1, that is, it shows the pdf for precipitation amounts that follow months of low precipitation. Similarly, the dashed curve shows the conditional pdf for category 5—it shows the pdf of precipitation amounts that follow months of high precipitation. According to Monte Carlo analysis, pdfs computed in this way are statistically distinct at the 99.9% confidence level if their means are separated by at least 0.03. The separation indicated in Fig. 1 is much larger than this. Indeed, all five conditional pdfs (one for each of the five categories) are statistically distinct at the 99.9% level, implying a nonzero level of predictability in the system—if precipitation is higher than average in 1 month, it is more likely to be higher than average in the following month, as well. The broad conditional pdfs have substantial overlap, however, suggesting that the associated level of predictability is very low. This is discussed further in section 5.

The conditional pdfs remain distinct even for later rainfall amounts. Figure 1b shows the means of the conditional pdfs for monthly precipitation 1 month, 2 months, and 3 months after the month used for the binning. For example, if the monthly precipitation in a given grid cell is very low—in the bottom fifth of all anomalies—the dotted line in Fig. 1b shows the expected value of the precipitation anomaly in that grid cell 1 month, 2 months, and 3 months later. Notice that even after 3 months, the pdf of rainfall is still affected by the initial anomaly. The separation of the highest and lowest conditional expected values at 3 months is statistically significant at the 99.9% level.

The possibility that this distinction stems from long-term trends in the precipitation was tested, at least partially, by repeating the analysis with detrended data. At each grid cell, the linear trend of precipitation over the 23 yr was determined through linear regression and then subtracted from the original data. The conditional pdfs (not shown) for the detrended data are just as distinct.

4. Model analysis

To examine whether or not the separation of the conditional pdfs in Fig. 1 results from land–atmosphere feedback, we employ a modeling approach similar to that used by Huang and Van den Dool (1993) and Koster et al. (2003). First we determine whether or not the behavior in Fig. 1 can be reproduced by a full AGCM. We then establish, through carefully designed simulation experiments, the mechanisms underlying the AGCM's behavior.

a. Models used

We use the National Aeronautics and Space Administration (NASA) Seasonal-to-Interannual Prediction Project (NSIPP) earth climate modeling system. As in Koster et al. (2003), the ocean component of the system is not used; instead, SSTs are prescribed to either observed values or to a climatological seasonal cycle (see section 4b). The AGCM, a state-of-the-art multilevel primitive equation model with a well-established climatology (Bacmeister et al. 2000), is run at a resolution of 2° latitude × 2.5° longitude. Coupled to the atmospheric model is the Mosaic land surface model (LSM), a soil–vegetation–atmosphere transfer model that includes an explicit treatment of subgrid vegetation heterogeneity (Koster and Suarez 1992, 1996).

b. Methods for prescribing variability

The model analysis relies on four separate 50-yr simulations with the land–atmosphere system. The simulations are defined as follows:

1) simulation ALO: the control simulation, including an interannually varying ocean surface and land–atmosphere feedback,
2) simulation AL: a simulation that includes land–atmosphere feedback but imposes a climatological seasonal cycle of SSTs,
3) simulation AO: a simulation with an interannually varying ocean surface but with land–atmosphere feedback artificially disabled, and
4) simulation A: a simulation with a climatological seasonal cycle of SSTs and with land–atmosphere feedback artificially disabled.

The design of these experiments follows exactly that used by Koster et al. (2000), who studied an analogous series of 4° latitude × 5° longitude experiments. A thorough discussion of the strategy can be found there. In essence, the four simulations allow us to quantify the relative contributions of ocean variability and land–atmosphere feedback to variability in precipitation and other atmospheric variables. Land–atmosphere feedback is disabled in simulations AO and A by prescribing at the land surface a (geographically varying) climatological seasonal cycle of evaporation efficiency. The climatological evaporation efficiencies were determined by processing multidecadal output from simulation ALO.

c. Results

As with all AGCMs, the statistics of simulated rainfall are far from perfect. Still, the AGCM successfully captures the broad structures of the observed mean and variance fields (Bacmeister et al. 2000; Koster et al. 2000, 2003) so that the simulated data should be acceptable for the present analysis. Impacts of the errors

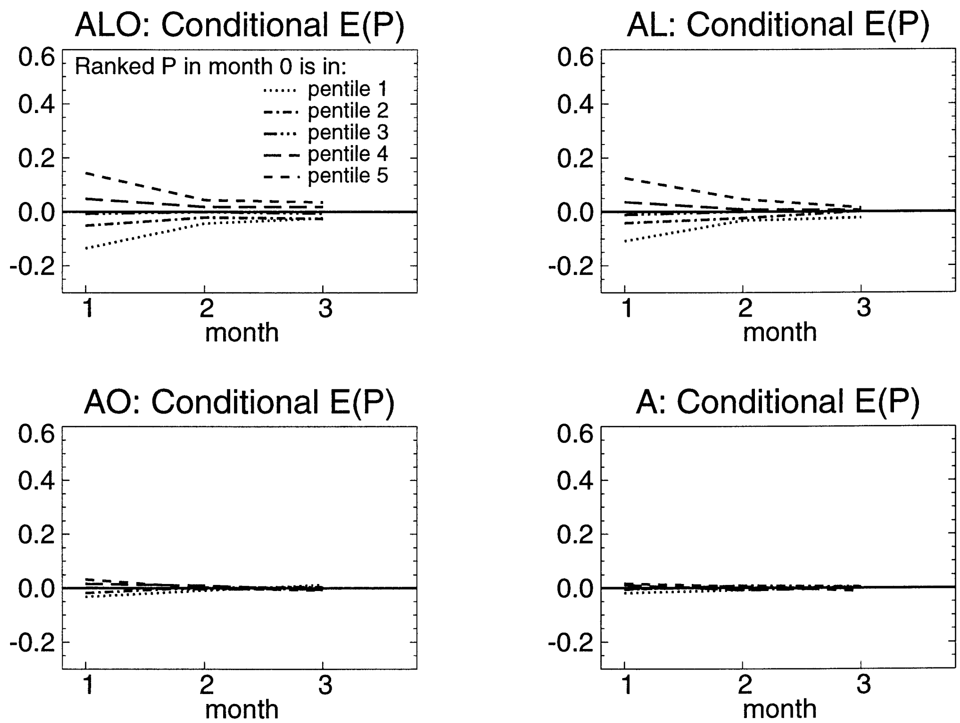

FIG. 2. Mean of the conditional pdfs as a function of time for each of the four AGCM experiments. Each curve shows the expected value of monthly rainfall 1, 2, and 3 months after an initial ranked anomaly.

are, in any case, arguably partially avoided through the standardization of the data—simulated means and variances are effectively removed from the AGCM precipitation rates through the application of (1).

Figure 2 shows, for each of the four experiments, the expected value of monthly rainfall for months 1, 2, and 3 conditioned on the anomaly in month 0. In other words, the figure shows, for the simulated data, the equivalent of Fig. 1b. As before, the data underlying each mean are taken from land grid cells in boreal midlatitudes (between 30° and 60°N), and month 1 can be May, June, July, or August. The slightly higher resolution of the AGCM relative to that of the observations results in a higher number of land cells (944) contributing to the model's statistics.

Clearly, the AGCM reproduces the character of the observed conditional means only when land–atmosphere feedback is enabled. The control simulation (ALO) shows a distinction in the conditional means very similar to, if slightly smaller than, that seen in the observations (Fig. 1b), as does the simulation with land–atmosphere feedback but without a variable ocean (AL). The slightly smaller distinction in the conditional means for the model may partly result from the slightly smaller size of the model's grid cell (see section 5). Both simulations without land–atmosphere feedback (AO and A) show little or no differentiation in the conditional means. Interestingly, simulation AO does show a small differentiation during the first month (significant at the 99.9% level), and the differentiation in simulation AL is slightly less than that in the control. Perhaps both land and ocean processes contribute to the distinction seen in simulation ALO early on. Certainly, though, land processes have, by far, the greatest impact on the positioning of the conditional pdfs.

5. Discussion

Not shown in Fig. 2 are the conditional pdfs for the simulated data, which (for simulations ALO and AL) are very similar to those for the observations (Fig. 1a). The broadness of these pdfs underscores the point, worth mentioning again, that the predictability associated with the distinction in these pdfs is very low—a statistically significant distinction does not in itself imply useful predictive skill. Fortunately, this need not reflect the upper limit of predictability associated with land–atmosphere feedback, for at least three reasons. First, the analysis above assumes a strictly local impact of soil moisture on precipitation. Precipitation, however, may be controlled as much by remote, large-scale patterns of soil moisture (and thus by remote patterns of antecedent rainfall) as by local conditions (e.g., Beljaars et al. 1996). Indeed, when either the observational data or the AGCM data are spatially smoothed prior to generating the pdfs, so as to account for feedback across larger spatial scales, the conditional pdfs are significantly more distinct (Fig. 3a). A more complex empirical method or a global seasonal prediction modeling system can better address the remote impacts.

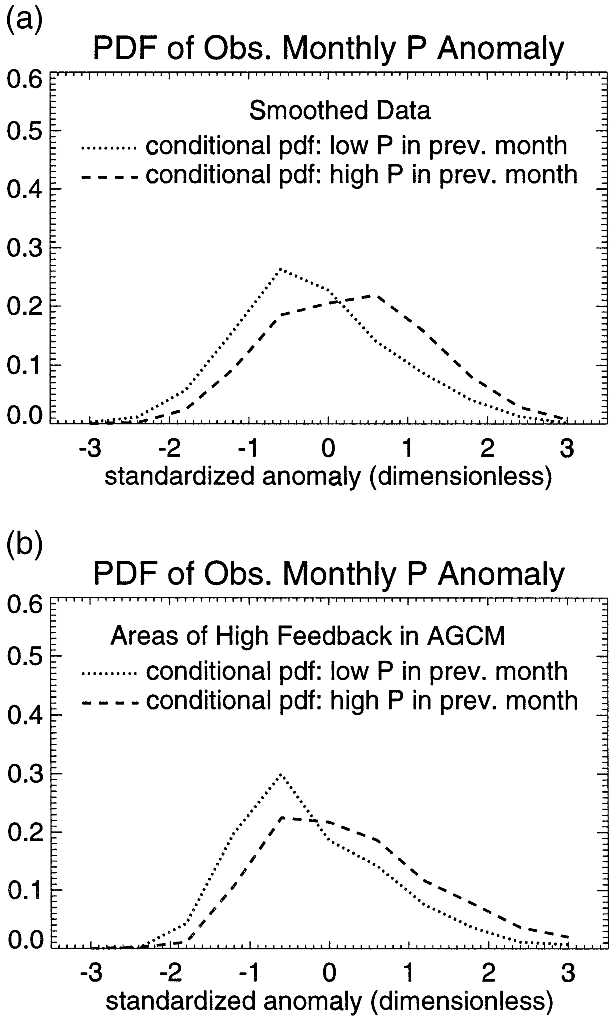

FIG. 3. (a) Conditional pdfs for standardized monthly precipitation anomaly in May, Jun, Jul, or Aug (as in Fig. 1a) obtained when a spatial smoothing with a nine-point filter is initially applied to the observational data. The ''spatial averaging'' scale of the observations is thus of the order of 1000 km. (b) Same as (a), except no smoothing is applied and only those land points indicated by the AGCM to have strong feedback contribute to the pdfs. The criterion for strong feedback is that the difference between the category 1 and 5 local (grid cell) conditional means for simulation ALO exceeds that for simulation AO by at least 0.75.

Second, the analysis above treated all midlatitude land grid cells equally. We know from past AGCM analyses (e.g., Koster et al. 2000; Koster and Suarez 2003), however, that some land regions are more amenable to land–atmosphere feedback than others. Up to now we have looked at all land grid cells to keep the observational analysis wholly objective and separate from the model analysis. When we limit the analysis to the 61 grid cells (mostly in the Great Plains of the United States) determined by the AGCM to be particularly strong areas of feedback, the conditional pdfs for the observations again become more distinct (Fig. 3b). It's worth noting here that the pdfs computed for areas outside of North America (e.g., throughout Asia; not shown) are still statistically quite distinct; the study area examined by Koster et al. (2003) is not wholly responsible for the distinction indicated in Fig. 1. The present analysis thus does extend the analysis of Koster et al. (2003) to global midlatitudes.

The comparisons in Figs. 1 and 2, by the way, are reproduced when considering the ''strong feedback'' regions or when spatial smoothing is applied. That is, the conditional means for the observations, now farther apart, are well reproduced only by simulations ALO and AL.

The third reason we are not evaluating the upper limit of predictability is that local land–atmosphere feedback relies on the soil moisture at the end of month 0, that is, at the end of the month used to define the conditional pdfs. Soil moisture at the end of a month, however, is not perfectly correlated with the total precipitation during the month. It is also affected by the precipitation's submonthly distribution and by interannual variations in radiation, wind speed, humidity, and so on. A seasonal prediction modeling system with a realistic land surface model can better capture these additional contributions to the initial soil moisture conditions.

Although the separation of the conditional pdfs in Fig. 1 is not a representation of maximum predictability associated with land–atmosphere feedback, it does allow an analysis of whether this feedback exists at all in the real world and whether it has any impact on the evolution of precipitation at seasonal time scales. Again, an impact of feedback on these time and space scales has never been clearly demonstrated with observational data. To summarize the present study, the expected value of monthly precipitation in the observational record is different for different values of antecedent precipitation. The AGCM reproduces this distinction in the conditional pdfs only when land–atmosphere feedback is allowed. In analogy with the results of Koster et al. (2003), this can lead to two possible conclusions: 1) land–atmosphere feedback does occur in the real world and can affect the pdf of precipitation even 3 months after an initial anomaly, or 2) the AGCM's fairly accurate reproduction of the observed behavior is a product of pure coincidence.

Conclusive proof of the existence of feedback in nature is therefore still elusive. The analysis above simply provides some intriguing supporting evidence.

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REFERENCES

Bacmeister, J., P. J. Pegion, S. D. Schubert, and M. J. Suarez, 2000: Atlas of seasonal means simulated by the NSIPP 1 atmospheric GCM. NASA Tech. Memo. 2000-104606, Vol. 17, 194 pp.

Barnston, A. G., and P. T. Schickedanz, 1984: The effect of irrigation on warm season precipitation in the southern Great Plains. *J. Climate Appl. Meteor.,* **23,** 865–888.

Beljaars, A. C. M., P. Viterbo, M. J. Miller, and A. K. Betts, 1996: The anomalous rainfall over the United States during July 1993: Sensitivity to land surface parameterization and soil moisture anomalies. *Mon. Wea. Rev.,* **124,** 362–383.

Findell, K. L., and E. A. B. Eltahir, 1997: An analysis of the soil moisture–rainfall feedback, based on direct observations from Illinois. *Water Resour. Res.,* **33,** 725–735.

——, and ——, 2003: Atmospheric controls on soil moisture–boundary layer interactions. Part II: Feedbacks within the continental United States. *J. Hydrometeor.,* **4,** 570–583.

Huang, J., and H. M. Van den Dool, 1993: Monthly precipitation–temperature relations and temperature prediction over the United States. *J. Climate,* **6,** 1111–1132.

Huffman, G. J., and Coauthors, 1997: The Global Precipitation Climatology Project (GPCP) combined precipitation dataset. *Bull. Amer. Meteor. Soc.,* **78,** 5–20.

Koster, R. D., and M. J. Suarez, 1992: Modeling the land surface boundary in climate models as a composite of independent vegetation stands. *J. Geophys. Res.,* **97,** 2697–2715.

——, and ——, 1996: Energy and water balance calculations in the mosaic LSM. NASA Tech. Memo. 104606, Vol. 9, 60 pp.

——, and ——, 2003: Impact of land surface initialization on seasonal precipitation and temperature prediction. *J. Hydrometeor.,* **4,** 408–423.

——, ——, and M. Heiser, 2000: Variance and predictability of precipitation at seasonal-to-interannual timescales. *J. Hydrometeor.,* **1,** 26–46.

——, M. J. Suarez, R. W. Higgins, and H. Van den Dool, 2003: Observational evidence that soil moisture variations affect precipitation. *Geophys. Res. Lett.,* **30**, 1241, doi:10.1029/2002GL016571.

Salvucci, G. D., J. A. Saleem, and R. Kaufmann, 2002: Investigating soil moisture feedbacks on precipitation with tests of Granger causality. *Adv. Water Resour.,* **25,** 1305–1312.

Van den Dool, H. M., 1985: Prediction of daily and time-averaged temperature for lead times of 1–30 days. Preprints, *Ninth Conf. on Probability and Statistics in Atmospheric Science*, Virginia Beach, VA, Amer. Meteor. Soc., 144–153.

——, W. H. Klein, and J. E. Walsh, 1986: The geographical distribution and seasonality of persistence in monthly mean air temperatures over the United States. *Mon. Wea. Rev.,* **114,** 546–560.